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EEG predicts the attention level of elderly measured by RBANS

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Abstract

Purpose – This study aims to investigate the correlation between neural indexes of attention and behavioral indexes of attention and detect the most informative period of brain activity in which the strongest correlation with attentive performance (behavioral index) exists. Finally, to further validate the findings, this paper aims at the prediction of different levels of attention function based on the attention score obtained from repeatable battery for the assessment of neurophysiological status (RBANS).

Design/methodology/approach – The present paper analyzes electroencephalogram (EEG) signals recorded by a single prefrontal channel from 105 elderly subjects while they were responding to Stroop color test which is an attention-demanded task. Beside Stroop test, subjects also performed RBANS which provides their level of functionality in different domains including attention. After data acquisition (EEG during Stroop test and RBANS attention score), the authors extract the spectral features of EEG as neural indexes of attention and subjects' reaction time in response to Stroop test as behavioral index of attention. Then, they explore the correlation between these post-cue frequency band oscillations of EEG with elderly response time (RT). Next, the authors exploit these findings to classify RBANS attention score.

Findings – The observations of this study suggest that there is significant negative correlation between alpha gamma ratio (AGR) and RT ($p < 0.0001$), theta beta ratio (TBR) is positively correlated with subjects' RT ($p < 0.0001$), these correlations are stronger in a 500ms period right after triggering the cue (question onset in Stroop test), and 4) TBR and AGR can be effectively used to predict RBANS attention score.

Research limitations/implications – Because of the experiment design, the pre-cue EEG of the next trail was very much overlapped with the post-cue EEG of the current trail. Therefore, the authors could analyze only post-cue EEG. In future study, it would be interesting to investigate the predictability of subject's future performance from pre-cue EEG and mental preparation.

Practical implications – This study provides an insight into the research on detection of human attention level from EEG instead of conventional neurophysiological tests. It has also potential to be used in implementation of feasible and efficient EEG-based brain computer interface training systems for elderly.

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Originality/value – To the best of the authors' knowledge, this study is among very few attempts for early prediction of cognitive decline in the domain of attention from brain activity (EEG) instead of conventional tests which are prone to human errors.

Keywords Elderly, Spectral analysis, EEG, Attention, Brain-computer interface, RBANS

Paper type Research paper

1. Introduction

Recent studies on treatment and enhancement of neurological conditions have shown a growing interest in employing computer-based technologies. Brain computer interface (BCI) system is of those techniques which has found a salient role in medical applications and cognitive training (Lee *et al.*, 2013; Lim *et al.*, 2012). It provides a feed-forward model in which subjects will learn a desired future behavior. The performance of such systems is highly sensitive to changes in user's attention level. In fact, attention variations affect the neurophysiological signal and thus the BCI performance. To build up adaptive training systems, it is of great importance to understand the correlation between neurophysiological signal and users' attentive behavior. In this work, we addressed this matter by processing the electroencephalogram (EEG) data recorded from healthy elderly subjects during an attentional task (Stroop color test).

By analyzing pre-stimulus EEG and its relation to subjects' performance, Hanslmayr and colleagues discovered that alpha, beta and gamma activity carry information of subject's attention state in such a way that increased pre-stimulus beta and gamma and decreased alpha is a predictor of high performance in a single trial (Hanslmayr *et al.*, 2007). Other similar studies confirmed that increased beta activity indicates attentional arousal (KAMIŃSKI *et al.*, 2012; MacLean *et al.*, 2012).

In addition to beta rhythm, interaction between alpha oscillation and attention has been also widely studied (Sharma and Singh, 2015). They mostly confirm that lower alpha activity reflects higher attentive behavior. Further comprehensive reviews can be found in (Klimesch *et al.*, 2007; Hanslmayr *et al.*, 2011; Klimesch, 2012).

In another study, researchers investigated the association between visual reaction time and EEG alpha band by analyzing the data recorded by Fz electrode (based on 10-20 system) from 14 young individuals (mean age: 22) (Jin *et al.*, 2006). Based on their task design, they defined different types of reaction time including immediate reaction time and movement time. They also extracted various parameters from EEG alpha band including peak alpha frequency and quality factor (peak frequency/band width). Their analysis suggests that there is a negative correlation between immediate reaction time and quality factor (Jin *et al.*, 2006). What is greatly missed in their work is consideration of the role of other frequency bands in reaction time.

Despite the huge number of studies on spectral analysis of EEG during cognitive processing, the exploration on time course of brain activity during executive control and neural correlates with behavioral index of attention, especially for a specific population like elderly, has been greatly missed. In this study, we used the data from 105 elderly subjects, recorded during Stroop color task, to investigate the above-mentioned gaps.

As a preliminary contribution, we reveal that interactions between frequency bands, defined as theta beta ratio (TBR) and alpha gamma ratio (AGR), carry information about elderly's response time (RT) in response to attentional tasks. Additionally, our results suggest that the most representative period of brain activity during executive function (the function that is activated by performing Stroop test) is a 500ms duration starting right after cue onset. Then, we exploit these findings to predict subject's attention level which is measured using repeatable battery for the assessment of neurophysiological status

(RBANS). Assessment of attentive function using EEG is a potential alternative for time-consuming neurophysiological tests with subjective scoring criteria.

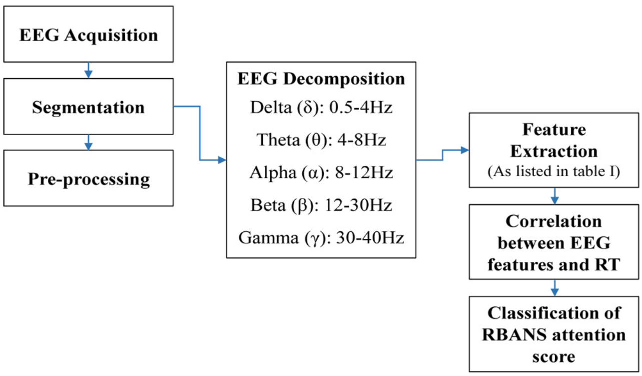
The rest of the paper is organized as follow. Section 2 describes the material and methodology used. The results of the study are presented and analyzed in Section 3. Finally, Section 4 discusses and concludes the study.

2. Materials and methods

An overview of the overall framework for the prediction of elderly attention level is shown in Figure 1. The first step is to record brain activity using EEG. Then, the EEG is pre-processed to remove artefact and noise. After pre-processing, the spectral features are extracted and a correlation analysis has been done to discover the most correlated EEG features with Elderly's RT (behavioral index of attention). Finally, these features have been used to detect the attention level of elderly. The following subsections describe the details of each step.

2.1 Repeatable battery for the assessment of neurophysiological status

RBANS is a clinical test that was introduced by Randolph *et al.* (Randolph *et al.*, 1998) specifically for two purposes including the assessment of cognitive decline in elderly and screening cognitive status in younger adults. The five cognitive domains that RBANS assesses are attention, language, visuospatial/construction, immediate and delayed memory. The administration and scoring of this assessment were done by research assistants who were trained in psychology and experienced in accomplishment of neurophysiological tests.



Notes: EEG was recorded by a single bi-polar channel during an attentional task and then decomposed into various frequency bands including delta, theta, alpha, beta, and gamma. Several spectral features including relative and ratio powers were extracted as neural indexes of attention. Since the subject's performance in response to attentional task (response time in this case) is behavioral index of attention, a correlation analysis between each of EEG features and response time was performed to find the most attention representative features. Finally, these findings were used for the classification of attention level based on the scores obtained from RBANS

Figure 1.
Schematic diagram of the overall framework

2.2 Task description

All subjects performed the Stroop color test which is a well-known task to study attention (MacLeod, 1991; MacLeod and MacDonald, 2000). It can be traced back to John Ridley Stroop who reported the Stroop effect in his work in 1935 (Stroop, 1935). Then, it gained great attraction in the fields of cognitive sciences and psychology such that a wide variety of experiments based on Stroop effect have been studied in these fields (Dyer, 1973; MacLeod, 1991).

During test, a colored word was presented on a screen and subjects were asked to name the color in which word is written. In fact, subjects were experiencing a conflict of information; what the word says and what is the color of the word. Thus, subjects needed to perform executive functions during Stroop color task (Marie, 2009).

Subjects underwent three sessions of the Stroop test in three different dates. Each session consisted of 40 repetitions and each repetition involved the Stroop test (attention trial) followed by a rest period (non-attention trial). Overall, each session took approximately 10 minutes. See Figures. 2 (a) and Figure. 2(b) to find the task protocol and Stroop test display.

2.3 Study population

The healthy participants, aged between 60-80 years old, were of Chinese ethnicity with literacy in English. They needed to meet the eligibility criteria including certain scores in clinical dementia rating, mini mental state examination, geriatric depression scale, etc.

2.4 Electroencephalogram acquisition

A wireless EEG setup was used to record the brain activity. In this setup, participants worn a headband with dry forehead electrodes (ground and sensor) connected to a computer/laptop via Bluetooth. The output EEG is from one bi-polar frontal channel at 256 sampling frequency.

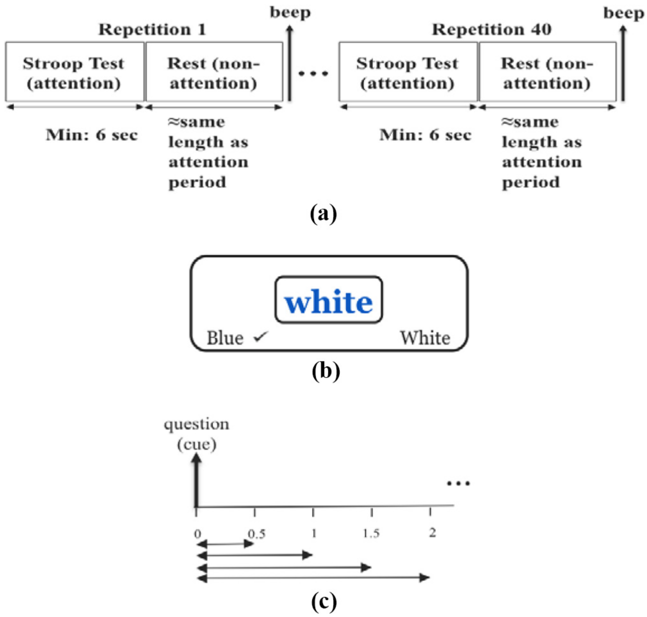


Figure 2.
(a) Recording protocol; Stroop test followed by a rest period; (b) an example of Stroop test demonstration; and (c) segmentation of EEG with reference to question onset

2.5 Electroencephalogram processing

Data first were band-pass filtered between 0.5-45Hz, then segmented into several time intervals including [0 0.5], [0 1], [0 1.5] and [0 2] second with reference to cue (question) onset in Stroop color task (see Figure 2(c)). Because of the large overlap between current trial's post-cue and next trial's pre-cue interval, we considered only post-cue EEG.

Data were visually screened to discard noisy trials. Additionally, trials with incorrect answers and those with RT value beyond the span of one standard deviation away from average RT were excluded from analysis. Eventually, we only considered trials with correct answer as attentional behavior.

After preprocessing, ten spectral features including relative and normalized ratio powers in delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz) and low gamma (30-45 Hz) frequency bands were extracted from segmented EEG as neural indexes of attention. To decompose EEG into frequency bands, Chebyshev type II filter has been applied. Table I lists the extracted features. In this table, T is total power which refers to the sum of five main frequency bands' powers.

2.6 Correlation

After EEG segmentations and feature extraction, we calculated the average of RT and spectral features over all segments for each subject. Thus, the number of total data points for correlation analysis is the same as the number of subjects (105). In fact, each data point conveys the information of one subject. Then, we explored the correlation of each spectral feature with RT using Spearman correlation.

2.7 Classification of RBANS attention score

Subjects were stratified into three classes based on their performance in RBANS attention domain. Table II shows the stratification criteria (Patton *et al.*, 2006). As the population of poor performers was relatively small, we excluded this group from classification. Thus, this is a binary

Table I.
Features definition

	Feature	Formulation
1	Relative delta power	$RDP = {}^{\delta}/_{T}$
2	Relative theta power	$RTP = {}^{\theta}/_{T}$
3	Relative alpha power	$RAP = {}^{\alpha}/_{T}$
4	Relative beta power	$RBP = {}^{\beta}/_{T}$
5	Relative gamma power	$RGP = {}^{\gamma}/_{T}$
6	TBR	$TBR = {}^{\theta}/_{\beta}$
7	Theta gamma ratio	$TGR = {}^{\theta}/_{\gamma}$
8	Alpha beta ratio	$ABR = {}^{\alpha}/_{\beta}$
9	AGR	$AGR = {}^{\alpha}/_{\gamma}$
10	Theta/(Beta+Alpha)	$TBAR = {}^{\theta}/_{\alpha+\beta}$

Table II.
Subject stratification based on RBANS attention score

Category	Score range	Size
Poor performance	<90	14
Average	90< <109	54
High performance	>109	37

classification task to discriminate between average and high attention levels. The method of linear discriminant analysis (LDA) with 10-fold cross validation was applied as the classification tool.

3. Results and analysis

3.1 Correlation between post-cue electroencephalogram biomarkers and response time

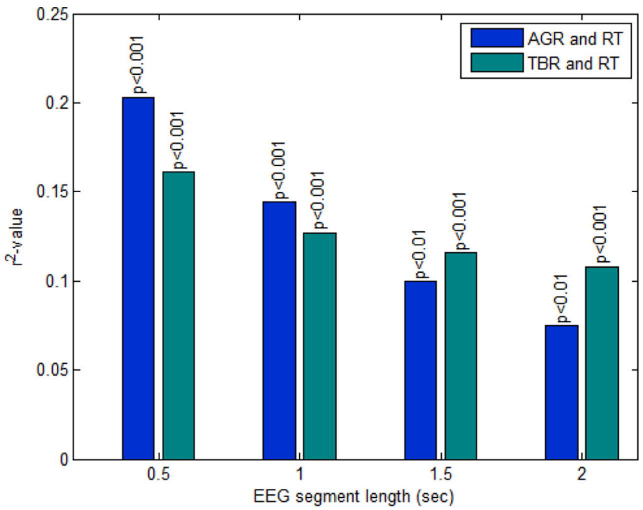
Based on the results, the engagement between alpha and gamma frequency bands in the frontal brain region is correlated with RT in a way that there is a significant negative correlation between AGR and RT ($p < 0.0001$). The outcomes also show that post-cue TBR is positively correlated with elderly's RT ($p < 0.0001$); higher beta and lower theta power result in a faster RT.

These observations reflect that although EEG frequency bands are not informative about RT on their own, the interactions between them (alpha and gamma/theta and beta) are significantly correlated with RT. As can be seen in Figure 3, these correlations are stronger in the duration of 500ms after the question onset than other time intervals.

Figure 3 depicts the correlation coefficient (r^2-value) between AGR and RT (blue) and TBR and RT (green) for different lengths of EEG time segments (0.5, 1, 1.5 and 2 second). Figure 4 shows the relationship between AGR and RT (bottom left) and TBR and RT (bottom right) in [0 0.5] second interval. Each data point is the representative of information for one subject.

3.2 The most informative electroencephalogram time segment

To investigate whether this observed difference is independent of segment length, we performed segmentation with the constant segment length of 500 ms using a sliding window with 50 per cent overlapping. Figure 5 shows the correlation coefficient (r^2-value) between AGR and RT (blue) and TBR and RT (green) for the fixed segment length of 500ms with reference to different start points. As can be seen, the results show that the value of correlation coefficient is independent of EEG segment length but dependent to temporal



Note: All segments start from time 0 (cue onset)

Figure 3. Correlation coefficient between AGR and RT (blue) and TBR and RT (green) for different EEG segment lengths

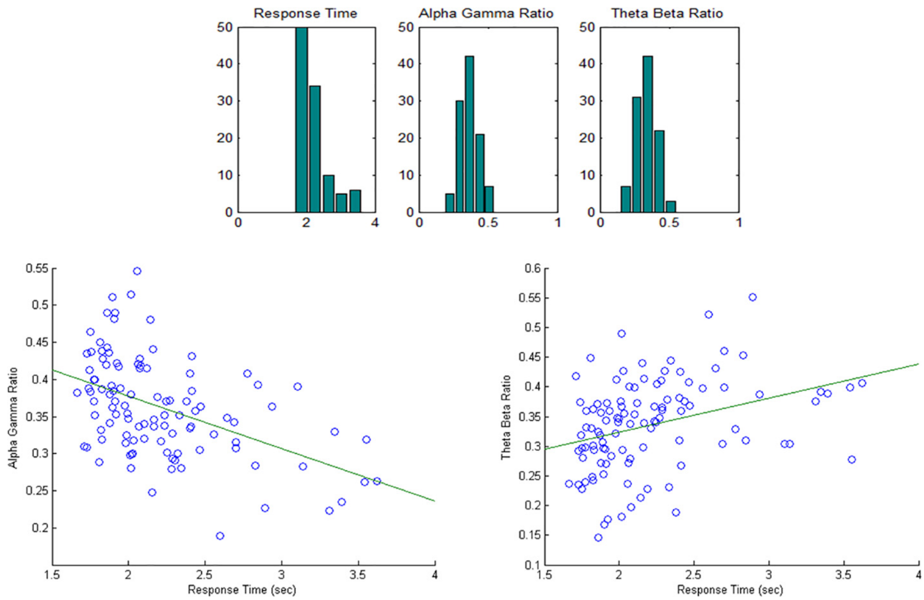


Figure 4.
Top: histogram of RT, AGR and TBR. Bottom: correlation between AGR and RT (left) and TBR and RT (right) in the interval of 500ms after cue onset

Note: Each data point belongs to one subject

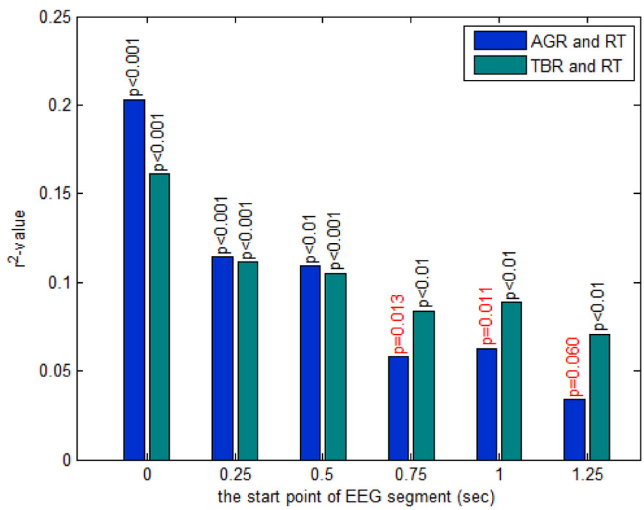


Figure 5.
Correlation coefficients between AGR/TBR and RT against the start point of EEG segment with reference to cue onset for a fixed segment length of 500ms

Note: The first bar shows the 500ms EEG segment starting from cue onset in which there is strongest correlation between TBR/AGR and RT points. The strongest correlation occurs in the duration of 500 ms starting from the cue. To avoid any overlap with the next cue, segmentation is done until one standard deviation away from average RT [2.20(average)-0.45(std) =1.75]. Thus, given the segment length of 500ms, the end point of horizontal axis would be 1.25.

This 500 ms period might be interpreted as the time course in which brain has higher activity in frontal area during executive function. This is a new critical aspect of analysis on neural mechanisms involved in cognitive control and executive function which needs further investigations. Previously, several studies have examined a relatively similar concern from the perspective of event related potentials. They mostly report the existence of a negative peak around 450 ms in response to Stroop color test (Markela-Lerenc *et al.*, 2004; Liotti *et al.*, 2000; Donohue *et al.*, 2012).

3.3 Spectrogram

For a better visualization of brain activity around cue onset and its changes by time over different frequency bands, the spectrogram of grand average over all trials and all subjects is depicted in Figure 6. Consider the EEG data are segmented into n segments. We define the segmented EEG as X in which segments are stored in columns:

$$X = \{x[1], x[2], \ldots, x[n]\} \tag{1}$$

Let us call the spectrogram of X as $\hat{X}$ whose columns are the short time Fourier transform (STFT) of X:

$$\hat{X} = F(X) \tag{2}$$

Each element in $\hat{X}$ corresponds to a point which is indexed by frequency and time such that its row indicates frequency index and its column shows time index. In fact, $\hat{X}$ is the frequency-time representation of X. Then, the power spectral density (PSD) of each element is calculated:

$$p(i,j) = P\left(\hat{X}(i,j)\right) \tag{3}$$

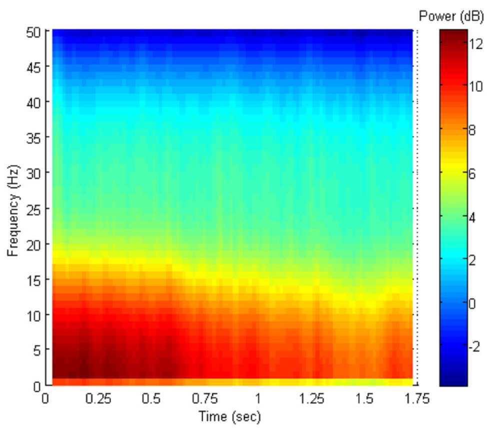


Figure 6.
Average spectrogram of EEG over all trials and all subjects

Finally, the grand average of PSD values is taken over corresponding frequency-time points to obtain the overall spectrogram as depicted in Figure 6.

The higher activity can be seen around cue onset (time 0) which continues till 0.5sec and then gradually decreases. The distribution of powers over different frequency bands in the interval of 0-500ms, comparing to other time courses, is in such a way that yields higher variations in TBR and AGR. As a result, stronger correlations could be captured between RT and EEG biomarkers extracted from this time course.

3.4 Classification of RBANS attention score using attentional indexes

After detection of EEG attention representative indexes by exploring the correlation between EEG spectral features and subjects behavioral performance in response to the attentional task (Stroop), we verify the findings by assessing the effectiveness of detected features in discrimination of subjects with different level of attentive function (based on RBANS score). Subjects are categorized into different classes as presented in Table II. Note that low performers are excluded because of the small sample size and therefore a binary classification is done. We performed classification with 10-fold cross validation using LDA once with all features (as listed in Table I) plus RT (11 features in total) and another time using only three features including TBR, AGR and RT (as attention-representative features). Table III compares the results. It can be seen than using TBR and AGR outperforms the classification with all features (+4.44 per cent). It reflects the importance of task-related feature selection and shows that the presence of irrelevant information degrades the classification accuracy.

4. Discussion and conclusion

In the present study, we conducted an investigation into the relationship between neural and behavioral markers of attention for elderly subjects. For this purpose, we extracted information from single frontal channel EEG recorded during an attention-demanded task, as neural marker, and explored how these EEG features are correlated with elderly's RT, as behavioral marker of attention. We also explored the time course of brain activity during executive function which has not been well addressed in the literature. Exploiting these findings, we further investigated whether EEG attention-representative features can replace RBANS (the traditional neurophysiological test) in identifying elderly individuals' attentive function level.

Reporting on the same task (Stroop) for the different population, it has been shown before that TBR is a discriminative feature to distinguish between attentive and non-attentive mental states (Fahimi F. *et al.*, 2017). Here, we showed that TBR is an attention-representative feature for elderly as well. In such a way that decrease in TBR is correlated with faster RT or, in other words, better performance in response to attentional task. We also showed that there is significant negative correlation between AGR and RT which might suggest that the engagement of alpha and gamma is a carrier of attentional information.

We also observed that the period of 500 ms after the cue onset is the most informative time course of executive function. To further investigate the characteristics of this time course, we calculated the spectrogram of EEG. The spectrogram of data supports that there

Table III. Results of RBANS attention score classification

Features	Accuracy (%)
All spectral features and RT	66.67
TBR, AGR and RT	71.11

is higher spectral activity around cue onset which lasts for approximately 500ms and then gradually diminishes over time. Further, using TBR and AGR extracted from EEG in this period for the classification of attention score obtained from RBANS verified the effectiveness of these features in attention measurement.

In line with our study, further research can be done to address whether pre-cue EEG encompass information about subject future performance to the cued task. Note that because of the experiment design we could only consider the post cue EEG. Another potential for future work is to take the subjective attention diversion into account. In this study, we simply considered trials with incorrect answers and suspicious trials, based on reaction time value, as outliers and excluded them from analysis. Future research is needed to investigate non-attentive trials based on information extracted from brain activity.

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